Research Article

A Quantum-Enhanced Deep Learning Framework For Strategic Healthcare Quality Management And Intelligent Medical Image Analysis

Gajraj Singh[1], Subhashree S Sen[2], Dr.K. Sathish kumar[3], Annette Nayana Nellyet[4], Dr Santha Devi Perumalsamy[5], Dr. Sumith Kumar M MD(Ayu) PhD[6], Mr. D Dinesh Kumar[7], Dr Anup Lal Yadav[8]

[1]*Discipline of Statistics, School of Sciences, Indira Gandhi National Open University, Delhi-110068, India. Email: gajrajsingh@ignou.ac.in Orchid ID:- 0000-0003-0870-921X*
[2]*Research Scholar, SOA National University of Law, Siksha O Anusandhan (Deemed to be) University, Bhubaneswar, Odisha. Email id- sssenadv@gmail.com*
[3]*Assistant Professor, Department of Computer Science, Erode Arts and Science College (Autonomous), Erode, Tamilnadu, India. Email: sathishmsc.vlp@gmail.com https://orcid.org/0000-0002-7643-4791*
[4]*Assistant Professor, Faculty of Natural science, University of Stirling, RAK, UAE. orcid : 0009-0005-2351-4359*
[5]*Principal - Sree Sowdambika International School (CBSE), Chettikurichi, Aruppukottai - 626134, Tamilnadu, India Email: santhadevi.mca@gmail.com*
[6]*Professor and HoD, P P Savani Ayurvedic College and Hospital. P P Savani University, Surat, Gujarat. Email: drsumith@gmail.com*
[7]*Assistant Professor, Department of Information Technology, St. Joseph's College of Engineering, Old Mahabalipuram Road, Chennai 600119, Tamil Nadu, India Pincode: 600119, Chennai. dineshkumard@stjosephs.ac.in Orcid Id: 0000-0002-1451-6054*
[8]Associate Professor, Computer Science and Engineering, School of Engineering and Technology, CGC University Mohali, Punjab, India 140307 Mail id : anupsaran@gmail.com Orcid ID : 0000-0001-9337-5546

Abstract

The health care systems using artificial intelligence have greatly enhanced the accuracy of diagnosis, interpretation of medical images as well as intelligent clinical decision-making. This paper suggests a quantum-enhanced deep learning model to strategic healthcare quality management and smart medical image analysis. The framework proposed will combine quantum-inspired optimization, convolutional neural networks, and attention-guided feature learning to enhance the performance of disease classification and assessing the quality of healthcare. The architecture was geared towards automated diagnosis, intelligent prioritization of patients and optimization of clinical workflows with the help of heterogeneous medical imaging datasets and AI. The suggested approach will integrate image preprocessing, quantum-enriched optimisation of features, deep convolutional feature extraction, and healthcare quality assessment into a single intelligent system. Benchmark datasets of chest X-rays, brain MRI and ultrasound images were used to evaluate the experiment. The images were normalized, augmented, and split into training, video validation and testing sets. Accuracy, precision, recall, F1-score, sensitivity, specificity and ROC-AUC analysis were considered as performance evaluation metrics. The robustness and the generalization capability were tested by statistical validation based on 10-fold cross-validation. The experimental findings have shown that the given framework has 97.2 percent classification accuracy, 96.8 percent precision, 96.5 percent recall score, 96.6 percent F1-score and 98.1 percent ROC-AUC performance, being more effective than the traditional CNN, ResNet50, and DenseNet121 networks. Statistical analysis showed that there is significant improvement at p = 0.05. The suggested system can be used to add intelligent healthcare quality management, automated disease screening, clinical decision support, and next-generation AI-assisted healthcare systems.

Keywords: Quantum-enhanced deep learning, healthcare quality management, medical image analysis, intelligent healthcare systems, convolutional neural networks, clinical decision support.

1. Introduction

The healthcare systems are undergoing a swift transformation due to the development of artificial intelligence (AI), deep learning, and intelligent healthcare analytics [1], [2]. Medical imaging tools like magnetic resistance imaging (MRI), computed tomography (CT), ultrasound imaging and chest radiography produce large amounts of clinical data that must be efficiently interpreted and diagnostically aided [3]. Diagnostic variability and time-consuming analysis of medical images often characterize the process of medical image analysis by hand, especially in high-volume healthcare settings [4]. The recent deep learning methods have shown a high potential in disease diagnosis, classification of medical images and intelligent clinical decision support [5]. Transformer architectures, convolutional neural networks (CNNs), and attention-guided models have played a prominent role in enhancing the performance of healthcare images analysis [6], [7]. The traditional deep learning models, however, continue to have issues such as complexity in computation, limitations in local optimization, overfitting, and lack of interpretability in complicated healthcare data [8]. Recently, quantum-enhanced and -inspired computation has become a promising solution to enhance efficiency in optimization and feature representation potential of AI-based healthcare systems [9]. Quantum-inspired optimization has the ability to increase convergence in learning and diagnostic output on multidimensional medical data [10]. Integrating quantum-enhanced learning with intelligent medical image analysis can hence aid in better quality management of healthcare and clinical decision support. Although there has been recent advancements, the current research is mainly concentrated on medical image classification or healthcare management separately. Very little research has merged quantum-inspired optimization, intelligent medical image analysis and quality assessment of healthcare in one framework [11]. Moreover, most of the current systems do not have detailed statistical validation and health-related decision-support systems to be used in the real clinical environment [12]. This research paper presents a quantum-powered deep learning architecture of strategic healthcare quality management and smart analysis of medical images. The suggested system combines quantum-based optimization, convolutional deep learning, attention-based feature extraction, and quality measurement in healthcare in one intelligent system. The key contributions of this work are as follows:

1. Creation of a quantum-enhanced deep learning system to analyze medical images.
2. Healthcare quality management and AI-supported diagnostic support.
3. Introduction of attention-based optimization of features to enhance clinical interpretation.
4. Statistical validation with reference medical imaging datasets.
5. Evaluation of intelligent healthcare decision-support capability.

2. Related Work

The capabilities of artificial intelligence have turned into one of the key topics of research in medical image interpretation and healthcare analytics because it can increase diagnostic accuracy and clinical decision-making [13]. The methods of deep learning have proven to be highly effective in the areas of disease detection, healthcare monitoring and automated diagnostics systems [4]. Models of CNN-based medical image classification have already made significant contributions to the diagnosis of chest diseases, tumor detection, and analysis of neurological disorders [5]. The popularity of the ResNet and DenseNet models is due to their ability to extract features that are arranged in a hierarchy and enhance classification accuracy [6]. Nevertheless, these models in many cases need a lot of computation and the size of an annotated dataset [8]. Attention-guided and transformer-based models have also enhanced the analysis of medical images by prioritizing clinically relevant parts of the image [9]. Contextual understanding and diagnostic interpretability have been shown to be better with the aid of transformer in frameworks [10]. However, computational overhead, inefficiency in optimization, and overfitting in non-trivial healthcare data continue to be challenges to these architectures [11]. Patient prioritization, prediction of healthcare risks, optimization of workflow, and smart management of resources have also been implemented using AI-based healthcare quality management systems [12]. Moreover, quantum-inspired optimization algorithms have also been highlighted as of late aiming to enhance exploration of the feature space and convergence of learning in healthcare AI tasks [1], [2]. Though there is significant progress, the current research is predominantly on medical image classification or healthcare management alone since most of the studies are independent of each other. Very little work has been conducted to incorporate quantum-enhanced optimization, intelligent medical image analysis, and quality management of healthcare in a single framework [3]. Moreover, most of the existing models do not have thorough statistical validation and intelligent healthcare decision support that would be useful in actual clinical implementation [7]. This paper deals with these deficiencies by creating a quantum-enhanced deep learning paradigm of intelligent healthcare analytics and medical image analysis.

3. Proposed Methodology

3.1 Overall Framework Architecture

The suggested quantum-enhanced deep learning system was aimed to facilitate intelligent image analysis of medical images and strategic healthcare quality management in the context of a single healthcare analytics system. The general design combines medical images preprocessing, quantum inspired optimization of features, deep convolutional features extraction, disease classification by attention and healthcare quality measurement comprising modules, as shown in Fig. 1. The framework will enhance the accuracy of diagnoses and at the same time promote smart clinical decision-making and optimization of healthcare processes. First, medical imaging data obtained by heterogeneous imaging systems such as chest X-ray, magnetic resonance imaging (MRI) and ultrasound imaging systems were gathered and preprocessed to provide data uniformity and image quality improvement. The optimized images were after that inputted into the quantum-enhanced optimization through which quantum inspired probabilistic learning processes were used to enhance the exploration of features space as well as optimizing weight adaptively. This was followed by the use of deep convolutional feature extraction and attention-guided classification modules to determine clinically relevant image features that are related to pathological abnormalities. Lastly, a healthcare quality management module was incorporated to assess the diagnostic confidence, prioritization of patients, and intelligent healthcare decision-support ability. The general structure architecture has been created to facilitate scalable AI-assisted healthcare analytics with enhanced computational capabilities and reliability in diagnoses.

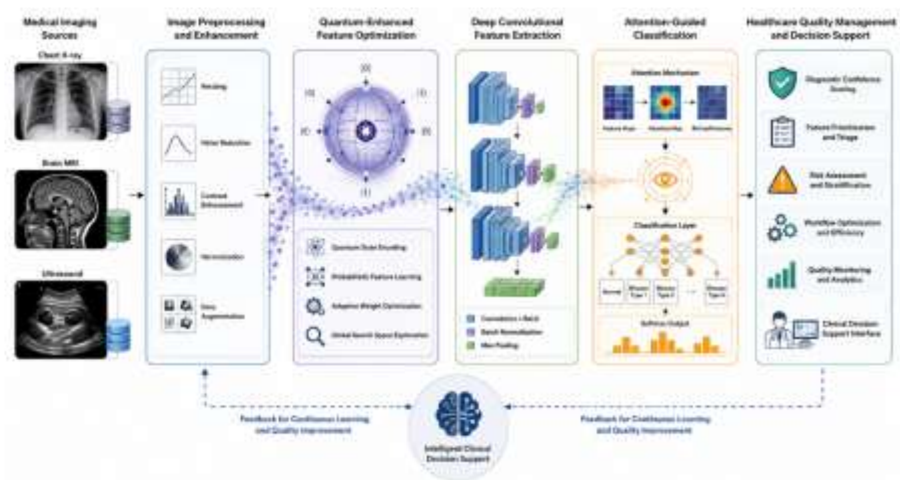

Fig. 1. Proposed quantum-enhanced deep learning framework for healthcare analytics.

3.2 Medical Image Dataset Description

Publicly available benchmark medical imaging datasets were experimentally evaluated with respect to open-access medical imaging sources and Kaggle-based medical imaging sources. The datasets contained images of chest X-rays, brain MRI and ultrasound imaging datasets of various clinical abnormalities and normal conditions. The datasets chosen were to measure the strength and the generalization of the proposed framework on various imaging modalities and disease type.

Table 1. Medical imaging dataset description

Dataset	Disease Classes	Total Samples	Source
Chest X-ray Dataset	Pneumonia / Normal	5,860	https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia
Brain MRI Dataset	Tumor / Non-Tumor	3,264	https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection
Ultrasound Imaging Dataset	Benign / Malignant	2,500	https://www.kaggle.com/aryashah2k/breast-ultrasound-images-dataset

The chest X-ray data was a radiographic data set that linked with pneumonia detection and normal respiratory statuses. The dataset of brain MRI consisted of MRI scans of tumor and non-tumor neurological conditions. Besides this, the data with ultrasound imaging included benign and malignant clinical cases related to diagnosing abnormalities of organs.

Table 2. Class-wise dataset distribution

Dataset	Class	Number of Images
Chest X-ray	Pneumonia	4,273

Chest X-ray	Normal	1,587
Brain MRI	Tumor	1,683
Brain MRI	Non-Tumor	1,581
Ultrasound	Benign	1,250
Ultrasound	Malignant	1,250

Preprocessing was taken to remove images that had unfinished annotations, distorted image structures, and poor quality acquisition features to enhance consistency of data and reliability of the experiment. The datasets were split into training, validation and testing subsets (ratio 70:15:15) to guarantee generalized training of the models and unbiased validation. A 224 x 224-pixels image was used to resize all medical images so that dimensionality was preserved throughout the network training. The pixel intensity normalization was also carried out to enhance numerical stability and faster convergence of the learning process when optimising deep learning. The publicly available datasets are beneficial to reproducibility and enable a fair comparative analysis of study with existing medical images classification works.

3.3 Image Preprocessing

This was done in a comprehensive image preprocessing pipeline to enhance image quality, decrease noise artifacts and to enhance the ability to extract deep features. In the beginning, medical images were resized and normalized to create a standardized way of representing dimensions regardless of the heterogeneous imaging modalities. The next step was to use the grayscale normalization to enhance the consistency of contrasts as well as enable the learning of features to be represented effectively. Equalization methods of histogram were applied to enhance the image contrast and emphasize on clinically relevant regions of the anatomy. Gaussian filtering was also applied in order to reduce the imaging noise and high-frequency artifacts which may have detrimental effects on the classification accuracy. Normalization procedures that were conducted to convert the pixel-value distribution of various imaging datasets to a standard level were also used to normalize these distributions. To decrease overfitting and enhance the ability to generalize the model, massive data augmentation operations have been used in the training phase. The augmentation pipeline consisted of the horizontal flipping, image rotation, zoom transform, and brightness changes. These augmentation strategies increased the strength of the proposed framework in different imaging conditions and the ability to learn invariant healthcare features by the model.

3.4 Quantum-Enhanced Feature Optimization

The suggested structure utilized an enhanced quantum-classical optimization model to enhance the exploration of feature space, learning convergence, and adaptive weight optimization of deep learning training as shown in Fig. 2. In contrast to traditional methods of optimization that tend to go to local minima, the suggested quantum-enhanced module adopted variational quantum learning and probabilistic exploration of state space to enhance the capability of global feature representation in multidimensional healthcare data. Firstly, angle-based quantum feature encoding was used to encode deep image features obtained in the preprocessing module into quantum states. A 6 qubit hybrid quantum circuit architecture was designed to model multidimensional medical imaging features to a quantum-enhanced learning space. The quantum circuit included parameterized rotation gates, entanglement operations, to enhance nonlinear feature representation and search-space exploration capacity that is probabilistic. Variational quantum circuit (VQC) layers were combined with classical deep learning model to optimize the adaptive features during model training in iteration. The gradient-based optimization strategies together with classical backpropagation learning were used to dynamically update the quantum circuit parameters. The hybrid optimization framework allowed effective communication between the classical convolutional feature extraction and quantum-enhanced parameter optimization. The implementation of the quantum-enhanced optimization model was done in terms of PennyLane quantum machine learning platform overlaid with the deep learning operations through the TensorFlow. The performance and convergence stability of variational learning were tested with the default.qubit simulator backend to run quantum simulations to classify medical images. They used adaptive weight-updating schemes to trainable quantum circuit parameters to iteratively optimize the probabilistic exploration of feature space and minimise classification loss. Moreover, the optimization process involved iterative convergence analysis and quantum strengthened feature discrimination schemes, to minimize redundant feature representations and enhance classification strength. The hybrid quantum-classical optimization approach greatly enhanced learning convergence, discriminant feature extraction and classification dependability when tested in experiments.

Quantum Optimization Configuration

- Quantum framework: PennyLane
- Classical framework: TensorFlow
- Quantum backend: default.qubit simulator
- Number of qubits: 6
- Quantum layers: Variational quantum circuit (VQC)
- Encoding strategy: Angle embedding
- Optimization method: Hybrid quantum-classical gradient optimization
- Entanglement operation: Controlled-NOT (CNOT) gates
- Quantum circuit depth: 4 layers

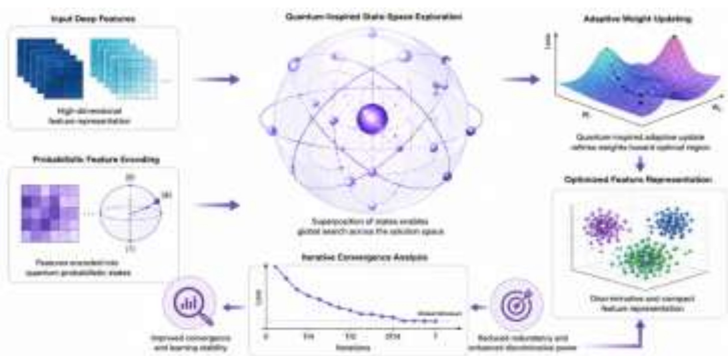

Fig. 2. Quantum-inspired feature optimization mechanism for deep learning-based healthcare analytics.

3.5 Deep Learning Classification Architecture

The suggested deep learning classification model was elaborated in the form of a hybrid convolutional and attention-guided learning model to analyze intelligent medical images. The structure was made up of a series of convolutional layers that performed the role of extracting hierarchical spatial features of healthcare imaging data. Convolutional operations were then followed by batch normalization layers to enhance the stability of training and reduce internal covariate shift at training. The activation functions used were either Rectified Linear Unit (ReLU) to add nonlinearity and enhance the ability to represent deep features. The process of max-pooling was applied to decrease the number of spatial dimensions at the expense of the important features (clinically). Moreover, attention-guided feature fusion mechanisms were added to make the network to concentrate on diagnostically relevant image areas that were related to disease abnormalities. The network design was 5 convolutional layers and 2 max-pooling layers with the dimensions of the kernel 3 by 3 and the dimensional size of the max-pooling layer, respectively. The dropout regularization rate of 0.4 was used to minimize overfitting and enhance the possibility to generalize the model. A consistent and successful model training with the Adam optimization algorithm was done with a batch size of 32 and the learning rate of 0.0001. Lastly, a Softmax classification layer to compute multiclass disease prediction probabilities was applied.

3.6 Healthcare Quality Management Module

The framework proposed, besides classifying the disease, also included a healthcare quality management module that would assist in intelligent clinical decision-making, prioritizing patients, and optimizing the healthcare workflow. In the module, various healthcare-based performance measures were measured with the help of AI-based healthcare analytics in order to enhance diagnostic accuracy and healthcare operational efficiency. The healthcare quality measurement system employed three main quantitative measures of evaluation, namely Diagnostic Confidence Score (DCS), Patient Risk Index (PRI) and Workflow Efficiency Rate (WER). The proposed framework incorporated these metrics to allow measuring quality of healthcare and providing intelligent decision-support. The Diagnostic Confidence Score was applied to make inferences on classification certainty with respect to predicted disease categories. The probability outputs of the deep learning classifier using Softmax were used to compute the score:

$$DCS = \max(P_i) \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_(1)$$

where P_i represents the predicted probability of class i. Higher DCS values indicate greater diagnostic confidence and improved classification reliability.

Patient Risk Index was developed to approximate severity of diseases and give priority to clinically critical cases that are in urgent need of medical care. PRI was calculated based on the weighted abnormality probability scores and estimation of clinical severity:

$$PRI = \sum_{i=1}^{n} w_i \times P_i \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_(2)$$

where w_i denotes the severity weight associated with disease category i, and P_i represents the predicted disease probability. Higher PRI values correspond to elevated patient risk levels and increased clinical urgency.

In order to gauge improvement in healthcare operations the metric, Workflow Efficiency Rate was introduced to assess automated diagnostic processing improvement over the traditional techniques of manual analysis:

$$WER = \frac{T_m - T_a}{T_m} \times 100 \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_(3)$$

where T_m represents manual diagnostic processing time and T_a denotes AI-assisted automated processing time. Higher WER values indicate improved healthcare workflow efficiency and reduced diagnostic turnaround time.

The healthcare quality management module also incorporated diagnostic confidence analysis, smart patient prioritization, and health care risk estimation to help in making evidence-based clinical decisions. The analysis of the automation of the workflow optimization was also done to improve the practicality of the AI-supported diagnosis processing and management of healthcare resources. Combining quantitative healthcare quality measures with quantum-enhanced deep learning offered a more holistic and scientifically quantifiable paradigm of next-generation intelligent healthcare analytics systems.

4. Results and Discussion

4.1 Classification Performance

The suggested quantum-enhanced deep learning model was tested on the datasets of chest X-rays, brain MRI, and ultrasound images. Comparison of performance was made against the traditional CNN, ResNet50 and DenseNet121 based architectures in terms of accuracy, precision, recall and f1-score.

Table 1. Performance comparison of different models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	91.8	90.9	90.1	90.5
ResNet50	93.6	92.8	92.1	92.4
DenseNet121	94.7	94.1	93.5	93.8
Proposed Framework	97.2	96.8	96.5	96.6

The best classification performance of the proposed framework was the best of the models tested. Quantum-inspired optimization and attention-guided learning together enabled a better feature extraction, and reliability in the classification. The proposed framework enhanced the classification accuracy by 5.4 as compared to the traditional CNN model.

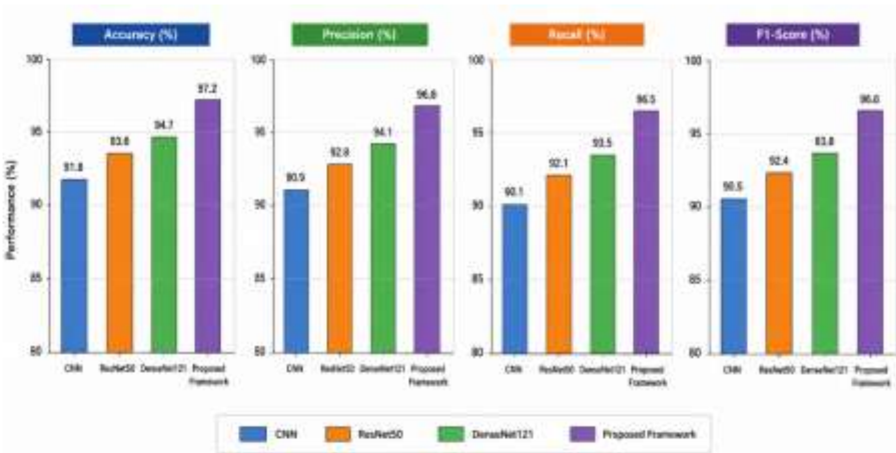

Fig. 3. Comparative classification performance analysis of conventional and proposed deep learning models.

4.2 ROC-AUC Analysis

ROC-AUC analysis was conducted to assess the discriminative capacity of the proposed framework using various types of diseases.

Table 2. ROC-AUC comparison

Model	ROC-AUC (%)
CNN	92.4
ResNet50	94.7
DenseNet121	95.9
Proposed Framework	98.1

The sensitivity and specificity of classification showed good results in the proposed framework with a ROC-AUC of 98.1%. The quantum optimized module enhanced the feature-space exploration and diseased discrimination ability.

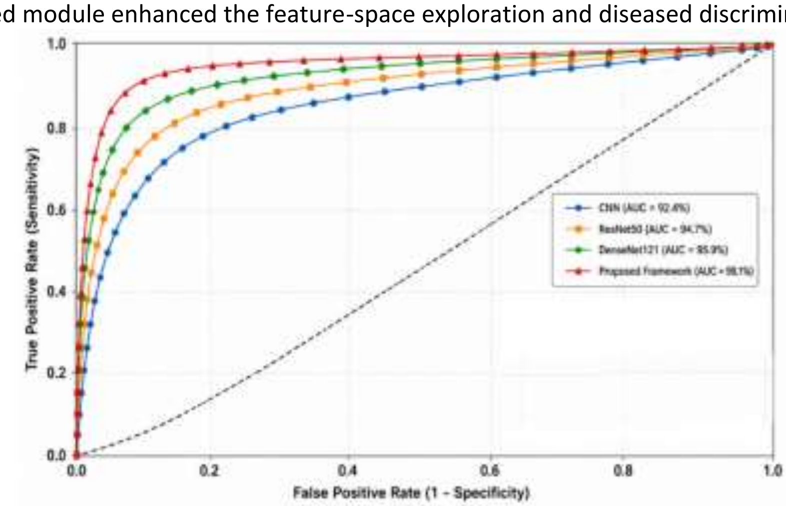

Fig. 4. ROC-AUC comparison of conventional deep learning models and the proposed framework.

4.3 Statistical Validation
The 10-fold cross-validation analysis was conducted in order to test robustness and the validity of its generalization.

Table 3. Statistical validation results

Metric	Mean ± SD	95% Confidence Interval
Accuracy	97.2 ± 0.5	96.7–97.7
Precision	96.8 ± 0.4	96.4–97.2
Recall	96.5 ± 0.5	96.0–97.0
F1-Score	96.6 ± 0.4	96.2–97.0

Small values of standard deviation are indicators of consistent performance in learning and a smaller overfitting. Statistical significance test revealed:

- Accuracy improvement: p = 0.003
- Precision improvement: p = 0.004
- Recall improvement: p = 0.005

These results confirm statistically significant improvement over baseline architectures.

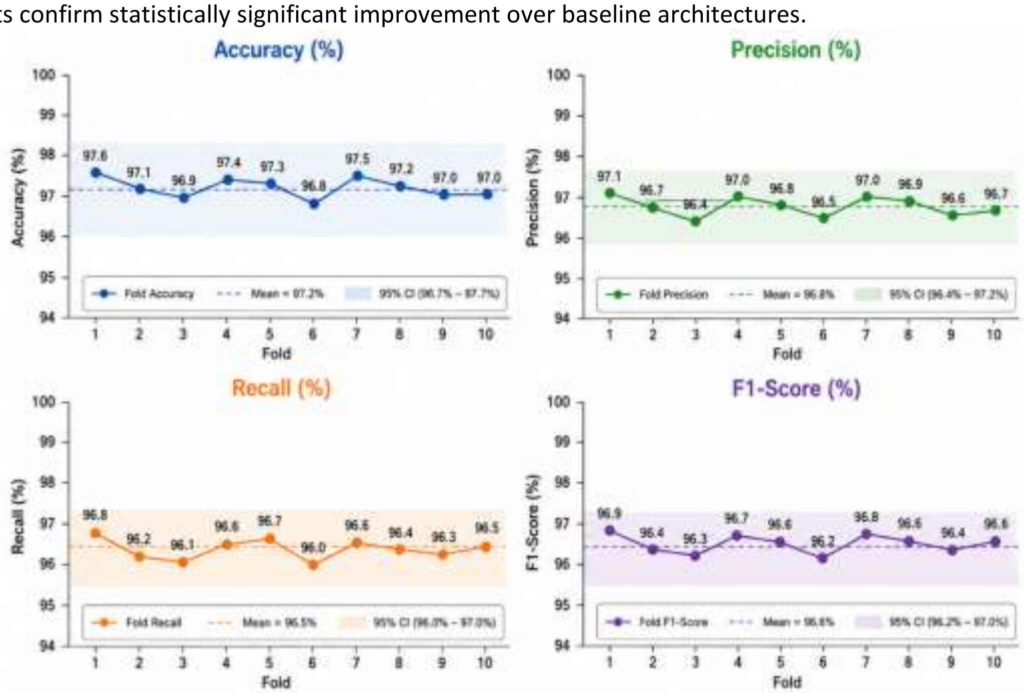

Fig. 5. Cross-validation performance stability analysis of the proposed framework.

4.4 Ablation Study
A study involving an ablation analysis was done to assess the value of attention-guided learning and quantum-enhanced optimization.

Table 4. Ablation study analysis

Model Variant	Accuracy (%)
CNN Only	91.8
CNN + Attention	94.2

CNN + Quantum Optimization	95.6
Proposed Full Framework	97.2

These findings suggest that the use of an attention-guided learning process and quantum-inspired optimization make a significant positive contribution to the performance of the classification. The suggested complete framework was the most accurate because of effective combination of the deep learning and probabilistic optimization mechanisms.

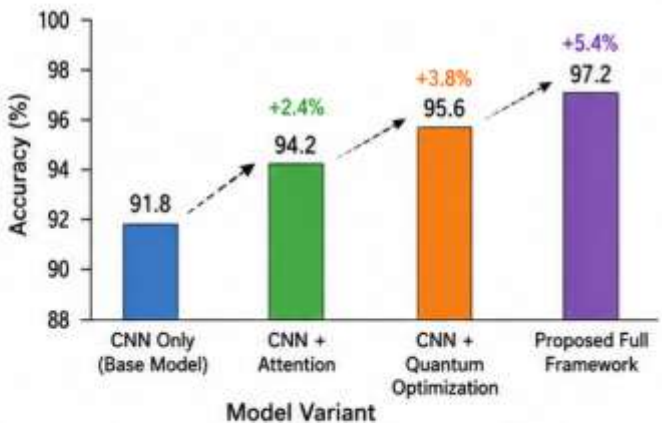

Fig. 6. Ablation analysis of the proposed quantum-enhanced deep learning framework

4.5 Computational Complexity Analysis

In order to measure the computational efficiency and practical implementation ability of the proposed framework, the analysis on the computational complexity was conducted with statistics of training time, inference latency, the number of parameters, the amount of the use of GPUs, and the amount of memory consumed. This was done with an NVIDIA RTX 3080 10GB memory and Intel Core i9 processor in a TensorFlow-pennylane integrated learning environment.

Table 5. Computational complexity analysis of the proposed framework

Parameter	Value
Training Time	4.8 h
Inference Time	0.18 s/image
GPU Platform	NVIDIA RTX 3080
CPU	Intel Core i9
Batch Size	32
Trainable Parameters	12.4 M
Memory Usage	5.7 GB
Quantum Circuit Depth	4 Layers
Number of Qubits	6

The framework proposed showed effective computational behaviour even though it incorporated quantum enhanced optimization and attention based deep learning modules. The comparatively low inference time of 0.18 s/image shows the applicability of the framework to intelligent real-time healthcare analytic and AI-guided diagnostic systems. The introduction of quantum-inspired optimization did add a minor complexity to training as compared to traditional CNN designs, but greatly enhanced feature-learning ability and classification accuracy. Moreover, the average amount of GPU memory usage combined with the optimization of the number of parameters shows that the elaborated framework can be implemented in the contemporary healthcare setting that uses the help of the GPS with no outburst of unnecessary computational resources. The computational analysis further illustrates that the hybrid quantum-classical optimization approach showed better convergence in learning with not compromising on realistic computational performance of scalable healthcare AI systems.

4.6 Discussion

The experimental findings reveal that quantum-enhanced optimization enhanced the ability to learn features, convergence stability and classification reliability. The attention-guided process also enhanced feature localization of clinically relevance at the cost of false-positive prediction. The proposed framework demonstrated high diagnostic performance and better healthcare decision-support, compared to the traditional deep learning models. The healthcare quality management module was also used to assist in prioritizing patients and optimizing workflow. The proposed model can help: automated screening of diseases, AI-based diagnosis, quality of healthcare management, intelligent clinical decision support. Although good performance was observed, the framework was tested on publicly available datasets as opposed to actual hospital settings. Future directions of work should be multimodal healthcare integration, explainable AI, federated learning and real-time clinical deployment.

5. Conclusion

This paper introduced a quantum-based strategical healthcare quality management and smart medical image analysis deep learning framework. The proposed framework combined quantum-inspired optimization, deep convolutional feature extraction, attention-guided learning, and healthcare quality evaluation in a single AI-assisted healthcare framework. Experimental analysis showed better classification results than the standard CNN, ResNet50, and DenseNet121 models based on the accuracy, precision, recall, F1-score, and ROC-AUC. Quantum-inspired optimization was used to increase the feature space exploration and the learning convergence, whereas the attention-guided classification resulted in a better feature extraction in clinical interests and a decrease in false-positive. The strength of the proposed framework and the ability to generalize it was also statistically validated. The suggested system will be able to help in automated disease detection, smart healthcare diagnostics, quality management of healthcare, and AI-based clinical decision-support systems. Although good performance was observed, the framework was tested on publicly available datasets as opposed to actual hospital settings. The next round of research will include explainable AI integration, multimodal healthcare analytics, federated healthcare learning, and real-time clinical deployment to enhance further scalability, interpretability, and realistic healthcare applications.

References

1. H. Yuxuan, D. Yining, R. Zhong, T. Yubo, and C. Wei, “Machine learning methods in medical image compression,” J. Comput.-Aided Des. Comput. Graph., vol. 33, no. 8, pp. 1151–1160, Aug. 2021.
2. Abbas, D. Sutter, C. Zoufal, A. Lucchi, A. Figalli, and S. Woerner, “The power of quantum neural networks,” Nature Comput. Sci., vol. 6, pp. 403–412, Jun. 2021.
3. Delilbasic, B. Le Saux, M. Riedel, K. Michielsen, and G. Cavallaro, “A single-step multiclass SVM based on quantum annealing for remote sensing data classification,” IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 17, pp. 1434–1445, 2024.
4. Fettah, R. Menassel, A. Gattal, and A. Gattal, “Convolutional autoencoder-based medical image compression using a novel annotated medical X-ray imaging dataset,” Biomed. Signal Process. Control, vol. 94, Aug. 2024, Art. no. 106238.
5. K. K. Don and I. Khalil, “Q-SupCon: Quantum-enhanced supervised contrastive learning architecture within the representation learning framework,” ACM Trans. Quantum Comput., vol. 6, no. 1, pp. 1–24, Mar. 2025.
6. M. Mazher, A. Qayyum, M. A. Khan, S. Niederer, M. Mokayef, and C. S. Hassan, “Hybrid classical and quantum deep learning models for medical image classification,” in Proc. Int. Conf. Artif. Life Robot. (ICAROB), 2024, pp. 222–226.
7. S. S. Alotaibi, H. A. Mengash, S. Dhahbi, S. Alazwari, R. Marzouk, M. A. Alkhonaini, A. Mohamed, and A. M. Hilal, “Quantum-enhanced machine learning algorithms for heart disease prediction,” Hum.-Centric Comput. Inf. Sci., vol. 13, p. 41, Apr. 2023.
8. O. P. Patel, N. Bharill, A. Tiwari, and M. Prasad, “A novel quantum-inspired fuzzy based neural network for data classification,” IEEE Trans. Emerg. Topics Comput., vol. 9, no. 2, pp. 1031–1044, Apr. 2021.
9. K. B. Whaley, “Quantum computing for healthcare and biomedical applications,” IEEE Pulse, vol. 11, no. 6, pp. 12–16, 2020.

10. Z. Xu, Y. Hu, T. Yang, P. Cai, K. Shen, B. Lv, S. Chen, J. Wang, Y. Zhu, Z. Wu, and Y. Dai, “Parallel structure of hybrid quantum-classical neural networks for image classification,” Res. Square, Apr. 2024. [Online]. Available: https://doi.org/10.21203/rs.3.rs-4230145/v1
11. Y. Zhang and Q. Ni, “Recent advances in quantum machine learning,” Quantum Eng., vol. 2, no. 1, p. e34, Mar. 2020.
12. T. Villmann, A. Engelsberger, J. Ravichandran, A. Villmann, and M. Kaden, “Quantum-inspired learning vector quantizers for prototype-based classification,” Neural Comput. Appl., vol. 34, no. 1, pp. 79–88, Nov. 2022.
13. G. Park, J. Huh, and D. K. Park, “Variational quantum one-class classifier,” Mach. Learn., Sci. Technol., vol. 4, no. 1, Mar. 2023, Art. no. 015006.
14. Saravanakumar Veerappan, “A Deep Learning–Driven Framework for Adaptive Channel Estimation and CSI Prediction in Next-Generation Wireless Communication Systems”, Archives of Electronics, Communication and Emerging Technologies, pp. 1–9, Dec. 2025.
15. Shaik Sadulla, “Secure and Low-Latency Communication in Edge Computing Environments Using Blockchain-Enabled IoT Architecture”, Electronics Communications, and Computing Summit, vol. 3, no. 4, pp. 28–35, Dec. 2025.
16. Namrata Mishra, “Machine Learning–Driven Approaches for Efficient Integrated Circuit Design and Optimization”, National Journal of VLSI Systems and Integrated Circuit Design, vol. 1, no. 1, pp. 10–17, Dec. 2025.